

# Developing the Ability to Manipulate Objects: A Comparative Study with Human and Artificial Agents

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## Introduction

In this study, we investigate whether and how human and artificial agents develop the ability to properly manipulate unknown objects (i) by discovering and exhibiting a set of functionally appropriate behaviours and (ii) by discovering the categories that group the objects that should be manipulated in the same way.

To achieve these goals, we created an *alien world* in which an agent (human or artificial) interacted with a set of objects (one at a time), which varied for a series of features, and was rewarded for manipulating them correctly. The features could be sensed directly (colour and shape) or perceived through interaction (inertia and “blinking”, i.e., colour intensity varying with movement). The agents' task was to infer how each object had to be manipulated.

Analysing the way in which the participants learn to solve the task we can verify to what extent the proposed artificial model approximates human behaviour. Moreover, by comparing artificial and human data, we also aim at identifying the role and the strength of the biases constituted by humans' previous knowledge. In particular, we investigate how much humans rely on previously learned “affordances”, that is, on associations between visual properties and motor responses acquired during experience (Gibson, 1979; Ellis and Tucker, 2000), and study the effect of previous experience on the developmental process.

We formulated the following predictions.

**Object properties.** We hypothesized that both artificial and human agents would first form categories on the basis of properties that can be sensed directly. We expected that for humans shape would be the most important feature, because it involves both visual and tactile systems and because novel nouns are typically extended on the basis of shape (see work on the so-called “shape-bias” by Smith, 2005).

**Association between objects and their manipulation.** In humans, we expected that specific movements would be associated with specific objects (e.g., circular movements would be associated with round objects).

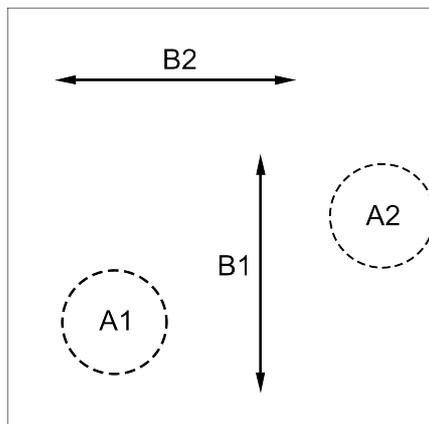
**Developmental process.** We expected that category development, in both human and artificial agents, would follow two qualitatively different processes: (i) the agents would first discover an appropriate

behaviour for an object and then apply it to other objects or (ii) the agents would learn a behaviour associated with a subset of features, and would gradually refine this subset. Regarding behavioural development, we expected that the agents (both human and artificial) would discover sub-optimal behaviour and apply it to more than one category, perhaps improving and differentiating the behaviour later on. We also expected that the discovery of a particular category-behaviour would facilitate the discovery of all others and particularly of the others belonging to the same family, because it would help the agents (i) pay attention to relevant features and (ii) hypothesize and test similar behaviours. Generally, we expected that the discovery of correct category-behaviours would positively influence the developmental process.

## Experimental scenario

The experimental scenario involved 16 two-dimensional objects that were to be properly handled. The agents could interact with one object at a time for a certain period and were rewarded with a score, ranging from 0 to 100, that measured how well they approximated the target behaviours. The agents did not know the number of objects, the fact that they were grouped in categories that required the same manipulation, and the number and type of behaviour that had to be exhibited. The objects were characterised by four binary features: two were *extrinsic* (directly perceived by the agents), that is, shape (circle/square) and colour (red/green); and two *intrinsic* (perceivable only through interaction), that is, inertia (light/heavy) and blinking (blinking/non-blinking). Each of the 16 objects, which were defined by all combinations of feature values, had to be manipulated according to its category. Only two (of the four) features were relevant for category membership. Thus, the objects were divided into four categories, one for each coupling of the binary values of the two relevant features, and each of which required a different manipulation (see Fig. 1). There were two types of required movements: placing the object in a target area (type A) and shaking the object (type B), and for each type two specific actions required (which target area or which shaking direction). The reward for categories A1 and A2 was proportional to the distance between the object and the target area at

the end of the trial (target areas were asymmetrical to prevent the human participants from using pre-acquired knowledge), whereas the reward for categories B1 and B2 was proportional to how closely the average object shaking amplitude approximated the desired one; the area in which the object was shaken was irrelevant. Although the objects were presented one at a time, for 30 seconds each, the agents could skip to the next object before the time expired.



**Figure 1.** Environment and target behaviours.

**Humans.** We asked the participants, who were seated in front of a computer screen, to interact with the objects by using the mouse. The left and right mouse buttons were used to skip to a new trial with a new or the same object, respectively. Participants were invited to “think aloud” during the experiment. Mouse and object tracks and participants’ speech were continually recorded. At the end of the experiment (which lasted 30 minutes), we interviewed the participants to collect additional data.

**Artificial agents.** The artificial agents were constituted by 3-layers neural networks with internal recurrent *leaky* neurons. Sensory neurons encoded the mouse and object XY positions, the shape of the object, and its RGB colour, whereas motor neurons encoded the XY mouse displacement and the skip-to-next-object functionality. The architecture of the neural network was fixed. The agents were trained using a trial and error process in which the free parameters (connection weights, biases, and time constants) were varied randomly; variations were retained or discarded depending on whether or not they led to improved average performance over the whole set of objects. Additional explanatory material is available from <http://laral.istc.cnr.it/esm/HvsA/>.

## Preliminary results

Although the two experimental settings were designed to be as similar as possible, some important differences should be considered in comparing the results.

The first difference is that the artificial agents have no previous knowledge (i.e. the free parameters that

determine how they react to experienced sensory states were randomly set). By contrast, humans possess highly structured capacities and knowledge that strongly affects the learning process. Even though the *alien world* scenario was designed to minimise the affect of humans’ previous knowledge in solving the task, evidence in pilot studies has shown that the effect persists. In keeping with our predictions, the results thus far indicate that humans tend to form categories first on the basis of differences in shape. Whether and to what extent this is due to the relevance of shape for interaction or to the association between shape and linguistic labels in humans will be explored in future experiments. Preliminary results also revealed a human tendency to associate specific movements with objects. Indeed, participants tended to use circular movements for circles and less-smooth movements for squares; moreover, squares tended to elicit placing movements. A second difference concerns the nature of learning processes. Artificial agents operate by introducing random variations and by retaining or discarding these variations on the basis of their overall effects. Humans instead use different mechanisms, which might vary among individuals, including the ability to focus on a particular object or groups of objects, to exploit the feedback provided after each trial, and to suddenly vary their behaviour. Furthermore, comparing the results obtained with human and artificial agents might allow us to understand whether the additional learning strategies possessed by humans enable or facilitate learning tasks that require previously acquired skills. Finally, preliminary results indicate that human participants who tend to verbalize more their strategies typically perform better than participants who do not verbalize them. Nevertheless, it is still unclear whether this advantage occurs because verbalization strengthens the capacity to memorise or whether it depends on the social context per se. Further experiments are planned to investigate how the social context (e.g., the presence of a co-learner, teacher, or simply others) influences which learning strategy is adopted. The presence of others could have many consequences. For example, it could increase the motivation to learn, help in overcoming individual resource limits (e.g., limits in working memory), and allow agents to share tasks (e.g., finding and sharing solutions among individuals adopting some form of communication).

## References

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